A METHOD OF REPRESENTING AND COMPARING EDDY CURRENT LISSAJOUS PATTERNS

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INTRODUCTION

In eddy current testing of heat-exchanger pipes the signal of the scanning probe is usually presented in the complex plane as a Lissajous curve. The size (amplitude) of the curve corresponds roughly to the volume of the defect. The phase is related to the depth of the defect and its location (inside or outside defects). Finally, the shape of the curve depends on the form of the defect.

The commercially available systems for EC inspection usually use only the phase and amplitude information. After the detection (with amplitude and phase thresholds), the defects are sized using calibration curves and the phase information. Such a system is not foolproof, usually because of incorrect or spurious defect detection. Therefore, in practice the classification made by the system is usually checked afterwards by a human operator. The operator can quickly determine whether the computer classification is correct just looking at the shape of the curve.

Use of only amplitude and phase information limits the capabilities of the system. For example, it is possible that defects can have the same phase indication and different depths. This can lead to defect over- or undersizing. Sometimes, however, the defect type could be determined based on the shape of the Lissajous curve and then either correction factors could be applied or different calibration could be curves used. Generally, the Lissajous pattern carries more information about the flaw than can be extracted using amplitude and phase only.

Systems that use the curve-shape information usually comprise various classifiers, which, after having been trained with example patterns, can categorize new signals into predefined classes. However, it seems that such systems are usually limited to applications in nuclear-power and aircraft industries. There the problem areas are relatively well defined, and there are resources available to gather enough data for training of the system.

In common inspection practice the problem is not so well defined, for example various types of heat exchangers with various types of defects can be inspected using the same inspection system. This means that there is always a possibility of coming across a defect type which did not occur before (and therefore was not in the training set) and which could be falsely classified. Classification into several predefined classes is therefore not so appropriate here. In such cases one could try to compare shapes instead of classifying them. Comparison can be used even when the number of example shapes is too small to construct a reliable classifier. Also, not recognized shapes are properly reported as such and not classified into a wrong category, as can be the case when classifiers are used.

An automated system could be constructed which would perform automatic evaluation of the defects it recognizes, and the remaining defects would be presented to the operator for the evaluation. The defects would be recognized by means of comparing their shapes to the example defects.

This paper presents a method for representing Lissajous curves and for comparing them which is based on the curvature of the curve. It also shows why the Fourier descriptors are not directly applicable for curve comparison.

COMMON METHODS OF LISSAJOUS-CURVE REPRESENTATION

As already mentioned most of the applications which look at the shape of EC Lissajous curves do it in order to perform some sort of classification. An input to the classifier, be it some statistical classifier or a neural network, consists of a feature vector. The feature vector has lower dimensionallity than the original Lissajous curve while representing the important characteristics of the curve. It is important that it fulfills the requirements of scale, rotation and translation invariance. It means that curves which differ only in amplitude, phase, and offset relative to the origin still have the same feature vector.

A method of obtaining feature vector most often encountered in the literature makes use of Fourier descriptors [1,2,3,4,5,6]. Other methods used include Tchebycheff coefficients [7], (extended) Freeman chain code [8], or various geometric shape parameters [9].

Fourier Descriptors

The Fourier descriptors are calculated as combinations of Fourier coefficients. For the calculation of the Fourier coefficients the curve is usually represented as a complex periodic function of its length [1]. Especially when the EC signal has been sampled in time and the probe has been pulled by hand this is the only option available. If sampling is equidistant then a curve can be represented as a complex function of sample position or time [10]. This second method is better because it can better distinguish between defects of various length.

In [1] it is shown that given Fourier coefficients $c_{n-1},\ldots,c_0,\ldots,c_n$, a set of Fourier descriptors:

$$b_n = \frac{c_{1+n}c_{1-n}}{c_1^2} \tag{1}$$

can be calculated, which are invariant under transformation as well as the choice of the starting point. Various other combinations of Fourier coefficients are possible which possess the same property.

Many articles [1,2,3,4,5,6] describe use of these Fourier descriptors for classification of EC Lissajous curves. They report good classification results. However, it is easy to notice

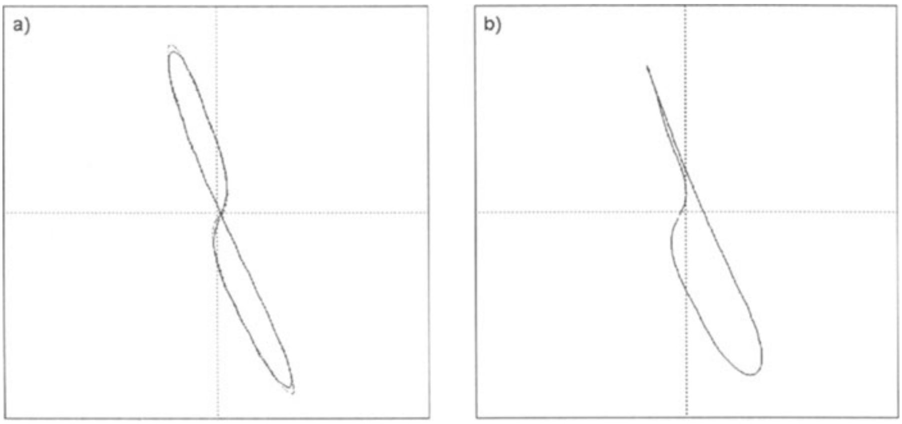

Figure 1. Two various curve shapes can have the same Fourier descriptors: a) original and resampled curve (17 Fourier coefficients), b) curve resampled from changed Fourier coefficients, but with the same Fourier descriptors.

in the equation (1) that different sets of Fourier coefficients (corresponding to different curve shapes) may give the same sets of Fourier descriptors (see figure 1 for example). This means that theoretically it is possible that completely different curves may be classified (using Fourier descriptors) into the same class. In other words the set of Fourier descriptors defined by equation (1) is not complete. If it were complete, then two curves would have the same shape if and only if they had the same set of Fourier descriptors.

For our application we had to compare Lissajous curves. The Fourier descriptor method despite its advantages, could not be directly used, because it did not guarantee correct distinction between various curves. To compare the Lissajous curves we have developed a method which uses the curvature of the curve.

CURVATURE REPRESENTATION OF A CURVE

A curve can be represented using its curvature. The curvature at a point on the curve can be defined in one of three ways [11]: (1) as a directional change in the tangent to the curve, (2) as the norm of the second derivative, and (3) as the inverse of the radius of the osculating circle touching the curve at a given point. In our case the curvature is approximated by the change of the direction of the curve (see figure 2) and can assume values between $-\pi$ and $+\pi$.

Figure 3a shows results of calculating the curvature for the original signal. The curvature is dominated by the changes of the direction resulting from the noise in the signal (especially around the origin). This noise could largely be removed by smoothing. However, there is another reason which makes the original signal unsuitable for calculating the curvature. The original curve is described by a variable number of not equidistant points. Because the curvatures are later to be compared, its is important that the curvature is known at a constant number of equidistant points along the curve. Therefore, before the curvature is calculated the curve is resampled from a limited number of Fourier coefficients. (The number of the coefficients used can vary depending on the complexity of the curve.) The Fourier coefficients are calculated from the unequally spaced points of the curve using the

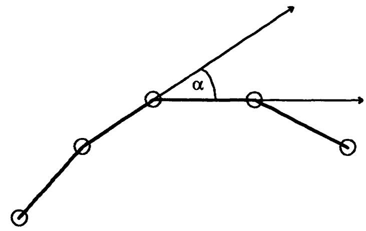

Figure 2. Curvature of a curve approximated by the change in its direction.

method described in [2]. Next the curve is reconstructed from the coefficients at a chosen number of equidistant points. Figure 3b shows the curvature calculated for the resampled curve.

COMPARING CURVES

Two curves which have the same shape will have the same curvature except for a shift caused by a different choice of the starting point of the curve. If the starting point is well defined (for example the origin for differential signals) then curvatures can be compared using simple correlation of data sets. Otherwise one has to assume curvatures to be periodic functions and calculate function correlation (using FFT for example) and find its maximum.

The result of the curvature comparison is a number which can be interpreted as a measure of similarity between the curves. For correlation equal 1.0 the curves are the same. With the decreasing correlation the similarity of the curves also decreases. However, lower correlation values also become less reliable as measure of curve similarity (or dissimilarity). The same correlation can be assigned to curves of which some are still similar to some example curve, while the other differ significantly from that curve.

This makes the choice of a threshold which decides when two curves are considered (almost) the same difficult. The threshold has to be chosen conservatively, otherwise curves differing too much would be accepted. At the same time curves which look similar are rejected, which is of course undesired. This problem is caused by the fact that correlation is

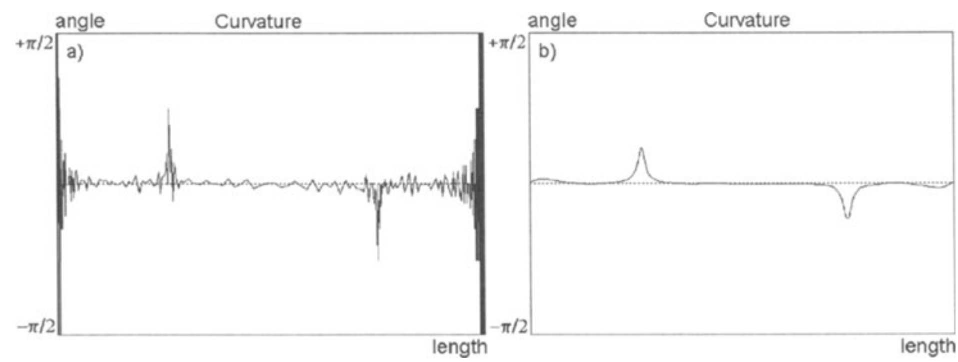

Figure 3. Curvature of the curve from figure 1a: a) calculated directly from the original curve, b) calculated from the resampled curve.

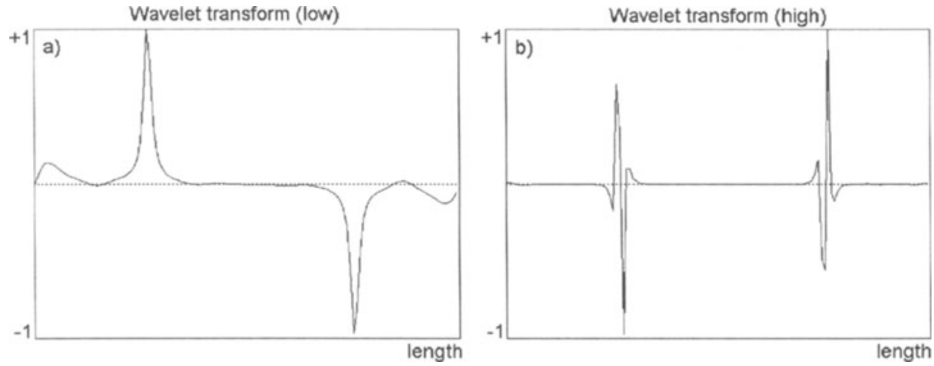

Figure 4. First stage of the wavelet transform of the curvature from 3b. Low frequency content a) and high frequency content b). Daubechies [12] orthonormal wavelet (N=3) has been used. The values are normalized.

only a global measure of similarity - a good match on some part of the curvature may (over)compensate for a bad match on the rest of the curvature.

The performance of the comparing algorithm can be improved if we make more information contained in the curvature visible for comparison using correlation An obvious information that can be useful is the position and sharpness of the bends in the curve. This information can be obtained looking at the high frequency content of the curvature.

A transformation which simultaneously extracts low and high frequency content of a signal is the wavelet transform. One stage of the wavelet transform pyramid [12] can be used to transform the curvature (figure 3b) into its low- and high-frequency components (figure 4). Each of the parts contains half as many data points as the original curvature, and the original curvature can be exactly reconstructed from the two data sets.

The curves can now be compared using correlations of low- and high-frequency curvature components. The experiments show that now the resulting value better captures the similarity of the curves. This in turn means that the accept/reject threshold can be set lower and more similar curves are correctly recognised as such, without risking false accepts.

CONCLUSION

A method of comparing Lissajous curves which is translation, rotation, and scale invariant has been presented. The method has been used in a prototype application and performs satisfactorily. However there are some problem areas:

- First, the algorithm requires some complex processing which takes time (mainly resampling of the curve). This is a problem because our goal would be to run the application (almost) on-line.

- Second, it has turned out that capturing similarity in a single value is difficult. That in turn makes the problem of choosing the accept/reject threshold not easy.

This has to do with the fact that generally determination of similarity is not a trivial problem. When humans compare shapes they often perform a selection of important features and ignore irrelevant ones. In the case of familiar shapes a classification into the same or different shape classes is done rather then comparison. In turn, when unfamiliar shapes are compared, the judgement is often a subjective one and there can be differences in opinion.

Research is currently being done in possibly better methods for curve representation and comparison. Among possibilities considered are Fourier coefficients, Fourier descriptors (we are going to look at the complete set of Fourier descriptors described in [13]), B-splines, moments of the curve, and shape features. Some of these methods are not inherently transformation invariant, therefore require either normalization or a more complex comparison algorithm. Quite possibly a combination of methods will have to be used, because none of the methods is without problems.

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